AUTOMATED ANALYSIS OF EDDY CURRENT SIGNALS IN STEAM GENERATOR TUBE INSPECTION

L. Udpa[1], P. Ramuhalli[1], J. Benson[2] and S. Udpa[1]
[1] Dept. of Electrical and Computer Engineering, East Lansing, MI, USA; [2] Electric Power Research Institute, Palo Alto, CA, USA

Abstract: Accurate and consistent determination of flawed regions in steam generator tubing is becoming increasingly important as nuclear power plants age and repair costs increase. The general problem of assessing the structural integrity of steam generator tubing using eddy current inspection is rather complex due to the presence of noise and interference signals under different inspection conditions. Additional difficulties in data analysis arise due to the fact that unwanted signals from support structures, probe wobble and geometry variations result in signals that are similar to defect signals. Automated analysis of eddy current inspection data from steam generator tubing is therefore becoming increasingly important to enhance the accuracy and consistency of signal interpretation. The feasibility of employing automated analysis systems for the interpretation of eddy current signals will be demonstrated and typical implementation results will be presented.

Introduction: Heat exchange tubes are used in a variety of industries for transferring heat to the fluid circulating outside the tube. A steam generator is a typical heat exchanger used in nuclear power plants. Steam generators (SG) transfer heat from the primary loop to the hot pressurized water circulating on the outside to produce steam, which is used to run the turbines. Steam generator tubes are continuously exposed to harsh environmental conditions including high temperatures, pressures, fluid flow rates and material interactions resulting in various types of degradation mechanisms such as mechanical wear between tube and tube support plates, outer diameter stress corrosion cracking (ODSCC), pitting, volumetric changes, primary water stress corrosion cracking (PWSCC), and inter granular attack (IGA). These flaws typically result in tube thinning and development of multiple crack-like flaws, thereby contaminating the fluids on the secondary side with the primary side coolant which is radioactive. Consequently, steam generator tubes in nuclear power plants are inspected periodically for cracks or leaks.

Multifrequency eddy current inspection techniques are currently among the most widespread techniques for the rapid inspection of SG tubing in the nuclear power industry. Multifrequency inspection has several advantages, including [1]:

- Collection of data at several test frequencies simultaneously decreases in-service inspection time and human exposure time to radiation.
- Allows separation of discontinuities that give dissimilar signals at different frequencies.
- Improves sensitivity to different types of discontinuities.
- Improves the detection and sizing of defects even in the presence of artifacts that complicate the analysis procedure.

Eddy current inspection has proven to be both fast and effective in detecting and sizing most of the degradation mechanisms that occurred in the early generators. Three major types of multifrequency eddy current probes are used in practice – the bobbin coil, the rotating probe coil (RPC) and the array probe. This paper describes an overview of automated analysis algorithms for data from these three probe types.

The paper is organized as follows. The next section describes the three different probe types, and the motivation behind the development of automated algorithms. Section 3 describes the various components of the analysis algorithms and presents typical implementation results. Finally, Section 4 summarizes the paper and presents directions for future research.

Eddy Current Probe Types: Three major types of multifrequency eddy current probes are used in practice for SG tube inspection. The first probe type is the bobbin coil probe, which consists of two identical coils connected in a differential mode and excited at multiple frequencies. The advantage of this probe is that its signal is resistant to various anomalous effects, such as probe wobble, temperature variations, and gradual variations in the inspected tube's electrical conductivity and diameter. This probe is very sensitive to abrupt anomalies, such as pitting, corrosion and fretting wear [2]. Although the bobbin coil probe is the most widely used probe, it has limitations in its ability to detect degradation in all regions of the tube (e.g., expansion transitions). Other limitations include the ability to accurately size and characterize degradation. As a result of these limitations, the bobbin coil probe is mainly used for the initial detection of possible degradation to quickly determine those areas of the tube requiring additional inspection with other types of probe that have improved ability to size and characterize degradation, such as rotating probes.

The rotating probe [3] typically consists of 3 different types of coils spaced 120^{o} apart (Figure 1a), rotating inside a tube at very high speeds (typically 900 RPM or higher) and moving forward in the axial direction. A typical configuration for the rotating probe uses two pancake coils and one plus-point coil. The plus point coil [4] consists of two coils that are oriented orthogonal to each other. Since the pickup coil configuration is differential, lift-off and magnetic effects due to geometry changes are significantly reduced, while axial and circumferential crack orientations are clearly distinguishable from each other. The rotating probe traverses the interior of the tube in a helical fashion, providing both axial and circumferential location information for any flaw. The helical scan pattern provides a higher resolution scan of the tube when compared to bobbin probes, and the data is in the form of an image (axial and circumferential position of the coil in the tube, Figure 1b). However, the inspection process is time-consuming and the amount of data generated can be large. For these reasons, rotating probe inspection is typically limited to small regions of the tube. The need for a high-resolution inspection of the entire tube, at speeds approaching bobbin probe inspection, has given rise to the third type of probe: the array probe.

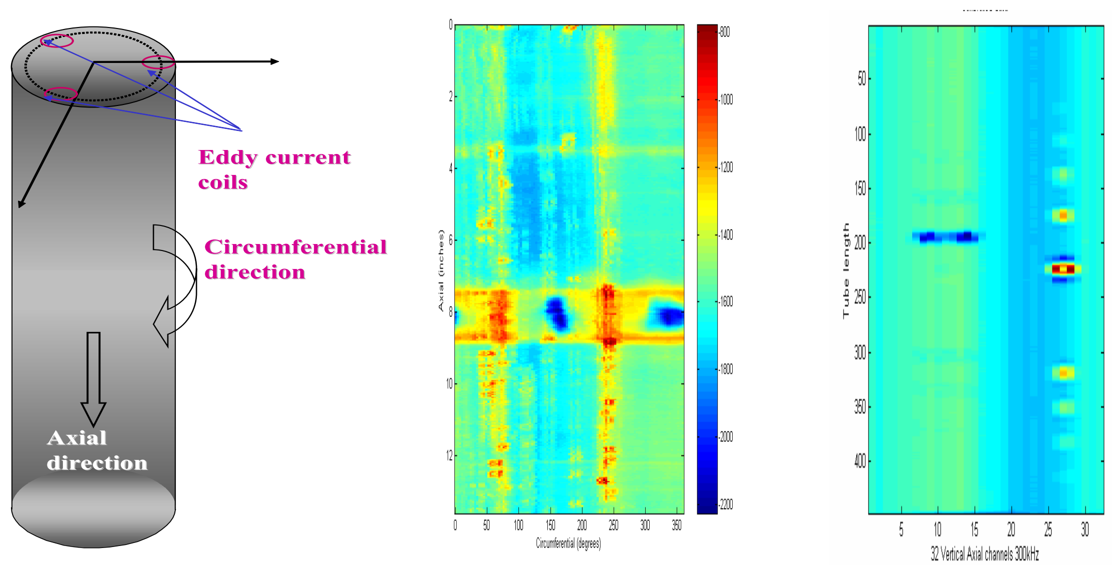
The array probe consists of multiple coils arranged around the circumference of the probe to facilitate 360^{o} coverage of the tube. Since the probe does not rotate, each coil is in the same relative position on the tube circumference, and the inspection takes a fraction of the time taken for rotating probe inspection. Again, the data is in the form of an image (Figure 1c). Most array probes consist of absolute multi-coil transmit receive probes. The probe typically also incorporates a standard bobbin coil probe in addition to the high resolution array.

A typical SG inspection can generate an enormous amount of data regardless of the probe type. The data must be analyzed in near real-time (as the data is being acquired). Generally, the analysis requirement is a classification of the signal into flaw and non-flaw categories, as well as an estimate of the flaw size for structural integrity calculations. Currently, eddy current data analysis is carried out by human analysts who use information present in the shape and phase angles of the signals. However, manual analysis, apart from being slow, is often not consistent and prone to operator fatigue. Thus, there is a strong need for the development of automated algorithms for the analysis of eddy current inspection data. An automated system for analyzing steam generator eddy current data provides significant cost savings associated with reduced analyst requirements and faster inspections [5, 6]. Additionally, the added consistency and accuracy that automated data analysis affords may allow utilities to demonstrate higher tube degradation detection probability and improved sizing accuracy. These capabilities could provide the basis for longer inspection intervals and the use of alternate repair criteria.

Although it is relatively easy to understand the basic eddy current probe-flaw interaction, real-world inspection data from steam generator tubes is difficult to analyze largely due to noise and many unwanted indications that cause significant distortion in the flaw signal. Several factors other than flaws can also influence the eddy current signal. These include the presence of external ferromagnetic support plates that hold the tubes in place, permeability variations in the tubes and external deposits. In addition, probe wobble and geometry variations result in signals that are similar to defect signals. Other measurement noise can also significantly affect the measurements. Successful detection and characterization of flaws requires a careful design of signal processing procedures to compensate for these effects.

Automatic flaw detection systems for bobbin coil eddy current data mainly focus on the relationship between flaw characteristics and the shape and the orientation of the corresponding Lissajous pattern of the eddy current signal [2, 3]. Development of analysis algorithms of rotating probe eddy current signals is relatively new. M. Hayakawa, et al [7], evaluated the characteristics of rotating eddy-current probe using 3-D edge-based FEM. B. Upadhyaya, et al [8] and Xiang et al [9] propose automatic diagnostics systems to analyze the rotating probe eddy current data using artificial intelligence techniques. In contrast to previous systems that use one dimensional (1D) signal features, these systems use both 1D and 2D signal features to identify defect types and to estimate defect parameters. However, analysis of array probe data in SG inspection appears to be relatively new, though there are several examples of analysis of array probe eddy current data in the literature [10, 11].

This paper presents an overview of automated analysis of eddy current signals obtained during SG tubing inspection. Algorithms for the analysis of data from all three types of probes – bobbin, RPC and array – are described. While the analysis algorithm for each probe type is different, the overall approach is similar, because the underlying physical process in each probe type is the same. Thus, in the paper, we present typical implementation results for only one type of probe – the rotating probe. Results for other probe types are presented in [12] and [13]. Figure 2 shows the overall schematic of an automated eddy current data analysis system. The different modules of the system are described briefly next.



(a) (b) (c)

Figure 1. (a) RPC configuration (b) Typical RPC data (c) Typical Array probe data.

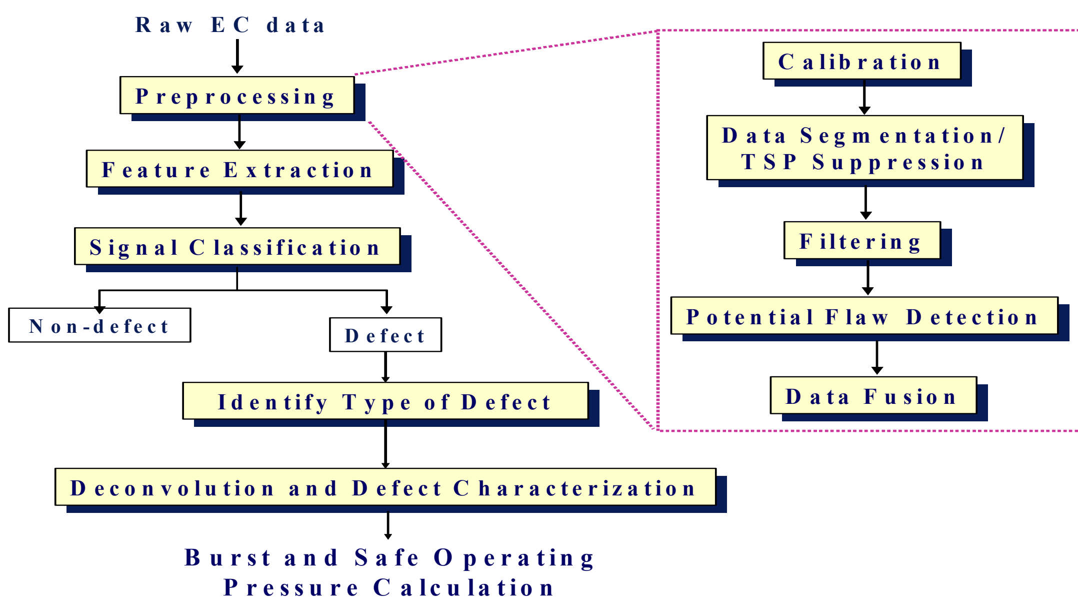


Figure 2. Eddy Current Data Analysis System.

Automated Analysis of SG ECT Data: The overall approach to eddy current data analysis is presented in Figure 2. The raw eddy current data is first applied to a preprocessing stage that filters the data and renders it insensitive to noise and other variations in the data acquisition process. A detection stage then identifies potential flaw indications. A set of features are then extracted from these potential flaw indications and applied to a signal classification block which identifies signals from flaws while minimizing the number of false calls (non-flaw signals which are identified as flaws). Depending on the application and probe type, further classification may be necessary to identify the specific damage mechanism. Finally, signals from cracks are applied to a flaw characterization routine that determines length, width and depth of the flaw, as well as the flaw profile. This information can be used to determine tube burst and safe operating pressures of the tube. Each stage of the algorithm is described briefly next.

Preprocessing: The first step in preprocessing is usually calibration of the instrument. The calibration procedure consists of two steps: phase rotation and voltage scaling. In order to correct for possible phase offset due to different probe response and instrumentation setup, a phase calibration process is applied in industrial practice. This is usually accomplished by setting the signal from a reference flaw to a given angle (for instance, rotating the 100% through-wall hole (TWH) signal to 40^0). Voltage scaling provides a consistent measure of signal amplitude for comparisons and involves normalizing the voltage of a reference signal to a specified value.

The next step is data segmentation and support suppression. Data from different locations in the tube have certain unique characteristics. Each region of the tube (TSP, tube sheet or TTS, the region between the supports or free span, U-bend, etc.) potentially requires a different set of preprocessing algorithms. In addition, flaw signals in the vicinity of external support structures (such as tube support plates, TSP) are distorted by the presence of the support structure. Support suppression enhances signals from flaws in this region, improving the overall probability of detection.

The segmentation algorithm depends on the type of probe used. For bobbin probes, the data is one-dimensional in nature (amplitude vs. axial position on tube), while for RPC and array probes, two-dimensional data is acquired (voltage amplitude as a function of axial and circumferential position). Thus, simple thresholding algorithms that detect the supports suffice for bobbin data. For RPC and array probes, more robust edge detection algorithms are required for accurately locating TSPs and segmenting the data. However, the support suppression algorithms in all cases are similar. Several different approaches, including simple linear mixing [14] and turbo mixing algorithms are most commonly used for TSP suppression. Other possible algorithms include non-linear mixing [15], blind source separation for separating the TSP and flaw signals from the measurement [16] and time-frequency approaches [17]. Optionally, filtering algorithms may be used to remove any residual TSP signals and other noise.

The last step in preprocessing is the identification of potential flaw signals. First, a threshold, computed using the statistical properties of the signals, is applied to identify potential flaw signals in data from all frequencies. Next, signals at different frequencies are integrated appropriately to determine the potential defect indications. However, the final result will contain signals from non-flaws as well (for instance, signals from external deposits). Thus, a classification algorithm is necessary to further reduce the number of false calls. Figure 3 presents typical results of preprocessing of RPC data. Figure 3a shows the raw eddy current data while Figures 3b and 3c show the data after calibration and support suppression. Figures 3d and 3e show the results of thresholding and identification of potential flaws.

Feature Extraction and Classification: Classification is the process of assigning signals into one of several known classes. Two major classification algorithms – neural networks and rule bases – are proposed in this paper. Features are first calculated for each potential indication obtained from the preprocessing stage. Three types of features are considered. The first set of features are physical features computed using the eddy current signal in the time domain. Examples of physical features include the peak-to-peak value of the real and imaginary components of the complex eddy current signal, the phase angle and energy. The second type of features is transform-based, and includes magnitude and phase spectra based on the Fourier transform. Finally, statistical features (such as the mean and variance) are also calculated. These features are calculated from each potential indication using data obtained at each excitation frequency.

Classification is accomplished using either neural networks or rule bases. A large training database of signals is used to train multilayer perceptron (MLP) neural networks using the backpropagation algorithm [18]. During testing, features are extracted from the unknown signals, and applied to the neural network for classification.

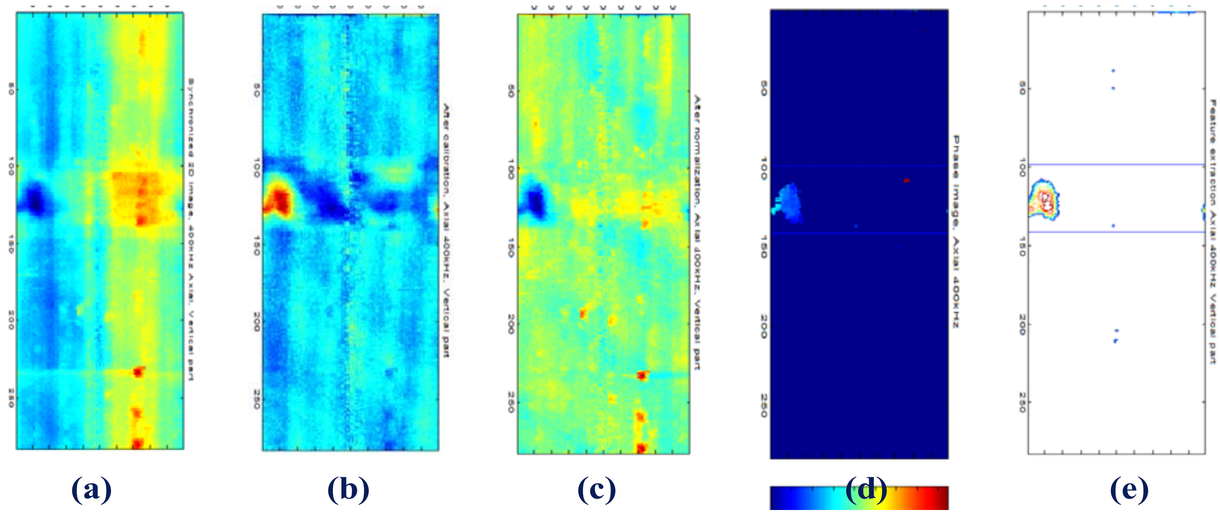


Figure 3. Results at various stages of preprocessing (a) Raw data (b) calibration (c) TSP suppression (d) thresholding (e) data fusion and potential flaw identification.

Similar training databases are used to obtain a set of decision rules that can accurately classify the data set. A decision tree induction algorithm called the ID3 algorithm [19] is used to obtain the rules. The rules are formed by conjunctions of simple propositions. An example of a simple rule is:

IF Phase_Angle > 0 AND Phase_Angle < 180, THEN classify signal as FLAW.

The overall classification algorithm is hierarchical in nature. After the training phase, data from unknown signals are first classified into two classes – flaw and non-flaw. Flaw signals are further classified according to the type of flaw (planar or volumetric). Finally, planar flaws are classified according to the orientation – axial or circumferential. Additional classes may be easily added as the algorithm is modular. Table 1 presents typical detection results of RPC data from three different databases, while Table 2 presents the number of false calls per tube. The detection percentage is seen to be around 90% with an average false call rate per tube of less than 1. These results indicate the feasibility of using such automated classification algorithms for the analysis of eddy current steam generator data.

Table 1. Classification results summary.

Dataset	Classification Scheme	# Flaws	# f laws Detected	% Detected
Data Set I	MLP NN	45	42	93%
	Rulebase		42	93%
Data Set II	MLP NN	35	31	89%
	Rulebase		31	89%
Data Set II	MLP NN	56	49	88%
	Rulebase		51	91%

Table 2. False call statistics.

Dataset	Classification Scheme	# Non-Flaw (NDD) Tubes	# NDD Tubes Correctly Classified	# False Calls	False Calls /Tube
Data Set I	MLP NN	23	19	4	0.17
	Rulebase		18	10	0.43
Data Set II	MLP NN	41	5	45	1.12
	Rulebase		20	46	1.14
Data Set III	MLP NN	85	71	21	0.25
	Rulebase		70	20	0.24

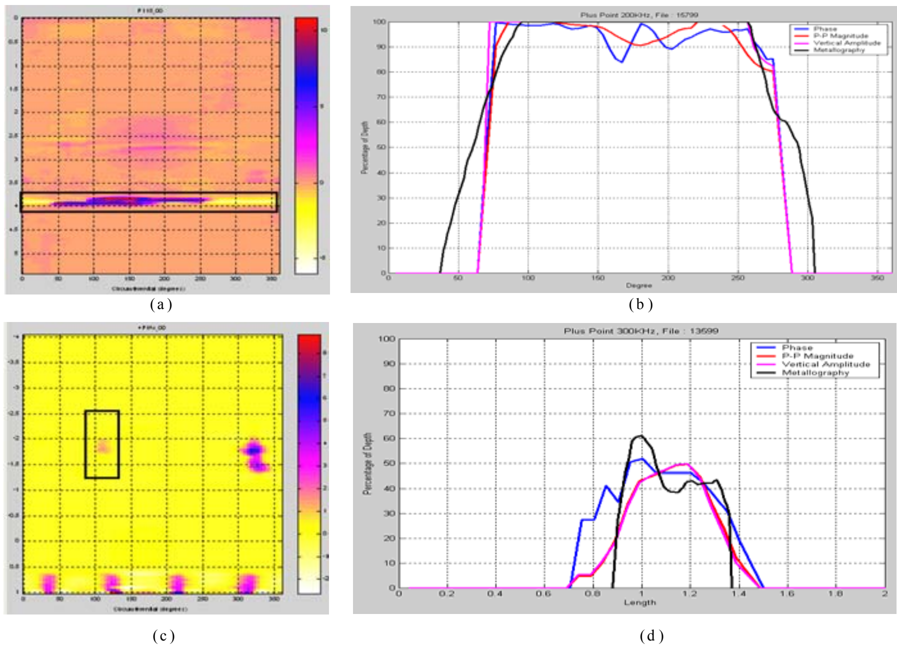


Figure 4. Flaw profiling: (a) Circumferential Defect (b) estimated and true flaw profile (c) axial flaw (d) estimated flaw profile.

Characterization: The last stage in the analysis is characterization. Flaw characterization involves determining the flaw shape and size. The simplest approach to characterization involves the use of calibration curves. In eddy current inspection, there is a relationship between phase angle of the flaw signal and flaw depth and location (ID or OD). This relationship may be represented by means of a calibration curve that maps phase angle to depth. The curve is obtained by using known flaws that are machined onto the calibration standard. Once the curve is obtained, the depth of unknown flaws may be estimated by calculating the phase angle of the flaw signal, and finding the depth corresponding to that angle by using the curve. In a similar fashion, an amplitude calibration curve that maps amplitude of the signal to depth may also be constructed. While the calibration curve is the most common approach in use and works well in practice, it has its drawbacks. The approach fails if signals from the unknown flaws are not similar to flaw signals used to create the curves. Further, this approach ignores the additional information present in the multifrequency measurements present. Finally, this approach does not provide a three-dimensional flaw profile. Other approaches that partially overcome these problems include the use of radial basis functions and wavelet neural networks [20]. Figure 4 presents an example of the characterization result. Figures 4a and b show the measurement signal and the true and estimated profiles for a 100% deep circumferential flaw, while Figures 4c and 4d present similar results for an axial flaw.

One of the major problems in defect characterization is that of "smearing" due to the finite size of the probes used for inspection. An eddy current C-scan image is representative of the plan view of a defect and can be expressed by a convolution of the true surface dimension of the defect with a kernel that is derived from the probe footprint. The accurate characterization of a defect profile therefore requires application of a deconvolution algorithm [9, 21] for removing the effect of probe geometry on the measured data. Deconvolution can also enhance the resolution of images from two closely spaced flaws. Figure 5 shows two sets of results, including the results of deconvolution applied to data from a 0.5" long flaw collected using a rotating probe. Before deconvolution, the length of the flaw as estimated from the data is 0.58", while the length after deconvolution is 0.5". Deconvolution is seen to significantly increase the accuracy with which the footprint of the flaw is determined. In addition, the application of deconvolution is seen to enhance the ability to separate out multiple flaws in close proximity.

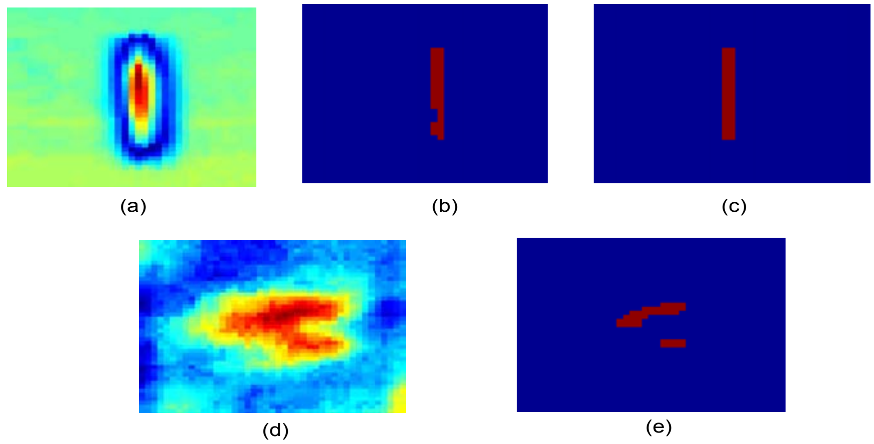


Figure 5. Deconvolution (a) original signal (b) flaw footprint for signal in (a) after deconvolution (c) actual flaw footprint (d) example of measurement from multiple flaws in close proximity (e) separation of multiple flaws after deconvolution.

Conclusions: This paper presented an overview of automated analysis algorithms for eddy current data analysis from steam generator inspection, along with typical analysis results. Analysis results show the ability of these algorithms to accurately identify signals from flaws while minimizing the number of false calls. A major advantage of using automated analysis is consistency and repeatability in the results, in addition to increased speed of analysis. The results also indicate that automated algorithms can be used to obtain accurate flaw profiles.

There are still several challenges that will need to be addressed before such analysis algorithms are widely used. Among the major challenges are:

- Generation of a sufficiently large database of signals for training the classification algorithms
- Obtaining confidence metrics for analysis results
- Development of efficient and robust data fusion algorithms that can combine information in several channels for improved classification and characterization.

These issues are the subject of on-going research activities.

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